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Application No.	2003/0437
Date of Filing	11 June 2003
Applicant	SCIENTIFIC SYSTEMS RESEARCH LIMITED, an Irish company of Unit 3, Howth Junction Business Park, Kilbarrack, Dublin 5, Ireland.

Dated this 4 day of February 2004.

An officer authorised by the
Controller of Patents, Designs and Trademarks.

2003/0457

FORM NO. 1

APPLICATION NO.

REQUEST FOR THE GRANT OF A PATENT
PATENTS ACT, 1992

The Applicant named herein hereby request

☒ the grant of a patent under Part II of the Act

the grant of a short-term patent under Part III of the Act

on the basis of the information furnished hereunder.

1. **APPLICANT(S)**

Name(s) and Address(s) and	**SCIENTIFIC SYSTEMS RESEARCH LIMITED** **Unit 3, Howth Junction Business Park** **Kilbarrack** **Dublin 5**
DescriptionNationality:	**an Irish company**

2. **TITLE OF INVENTION**

"A Method for Process Control of Semiconductor Manufacturing Equipment"

3. **DECLARATION OF PRIORITY ON BASIS OF PREVIOUSLY FILED APPLICATION FOR SAME INVENTION (SECTIONS 25 & 26)**

Previous filing date	Country in or for which filed	Filing No.
NONE		

4. **IDENTIFICATION OF INVENTOR(S)**
Name(s)/Address(es) and Nationality of person(s) believed by Applicant(s) to be the inventor(s)

1. Hopkins, Michael
2. O'Leary, Kevin
3. Scanlan, John

1. 46 St. Margarets Avenue, Raheny, Dublin 5, Ireland
2. 14 Esker Meadow Lawn, Lucan, County Dublin, Ireland
3. 50 Summerville Avenue, Waterford, Ireland

5. **STATEMENT OF RIGHT TO BE GRANTED A PATENT (SECTION 17(2)(B))**

By virtue of a Deed of Assignment effective June 11, 2003

6. **ITEMS ACCOMPANYING THIS REQUEST - TICK AS APPROPRIATE**

(i)	☒	prescribed filing fee (€125.00)
(ii)	☒	specification containing a description and claims
	☐	specification containing a description only
	☒	Drawings referred to in description or claims
(iii)	☒	An abstract
(iv)	☐	Copy of previous application(s) whose priority is claimed
(v)	☐	Translation of previous application whose priority is claimed
(vi)	☐	Authorisation of Agent (this may be given at 8 below if this Request is signed by the Applicant(s))

7. **DIVISIONAL APPLICATION**

The following information is applicable to the present application which is made under Section 24 -

Earlier Application No:
Filing Date:

8. **AGENT**

The following is authorised to act as agent in all proceedings connected with the obtaining of a Patent to which this request relates and in relation to any patent granted -

Name	**Address**
F. R. KELLY & CO.	at their address as recorded for the time being in the Register of Patent Agents

9. **ADDRESS FOR SERVICE (IF DIFFERENT FROM THAT AT 8)**

SCIENTIFIC SYSTEMS RESEARCH LIMITED

F. R. KELLY & CO.

By: ____________________
EXECUTIVE

Date: June 11, 2003

JUN 2003

A Method for Process Control of Semiconductor Manufacturing Equipment

BACKGROUND OF THE INVENTION

FIELD OF THE INVENTION

The present invention relates to a method for process control of semiconductor manufacturing equipment.

PRIOR ART

The manufacture of integrated circuits is a detailed process requiring many complex steps. A typical semiconductor manufacturing plant (or fab) can require several hundred highly complex tools to fabricate intricate devices such as microprocessors or memory chips on a silicon substrate or wafer. A single wafer often requires over 200 individual steps to complete the manufacturing process. These steps include lithographic patterning of the silicon wafer to define each device, etching lines to create structures and filling gaps with metal or dielectric to create the electrical device of interest. From start to finish the process can take weeks to complete.

Faults can and do occur on these manufacturing tools. A fault on a single wafer can compromise all devices on that wafer and all subsequent steps on that wafer may be worthless and the wafer scrapped. Thus, timely and effective fault detection is a necessity. An example semiconductor manufacturing tool is depicted in Fig. 1 and shows a process chamber 1, a substrate to be processed 2, process inputs or set-points 3, tool-state and process-state sensor outputs 4 and a data collection interface 5.

The manufacturing tools are complex and many different faults can occur, some specific to the tool process, that impact tool productivity and yield. As an example of the type of faults that can occur, consider a thermal chemical vapour deposition (CVD) tool, used to deposit layers of semiconductor or dielectric materials in the device manufacture. The quality of the process is determined by the output, measured by some metrics such as film uniformity, stress and so on. The quality of the output in turn depends on the process inputs, for example gas flow rates, reactor pressure and temperature in the case of the thermal CVD tool. If there is a deviation in any of the process parameters, then the quality of the output may be negatively impacted.

Another type of fault concerns excursions in the process itself. There are many examples, including a compromise in chamber vacuum, a change in reactor wall conditions or chamber hardware, an electrical arc or even a problem with the incoming wafer. Again the quality of the output will be affected with possible impact on tool yield.

A common feature in all of these faults is that sensors on the tool will generally indicate a change in system state, although this does depend on the sensitivity of the tool sensors. The manufacturing tools are typically equipped with tool-state sensors, for example gas flow meters and pressure gauges, and process-state sensors, for example optical emission detectors and impedance monitors. If a process input changes, then, generally, some of the tool sensors will register that change. If the process reactor conditions change, again the tool sensors will register a change.

The most common approach to process control and fault detection on semiconductor manufacturing tools is Statistical

Process Control (SPC), whereby many if not all of the process inputs are recorded and control charts are monitored for out-of-control events. Fig. 2 shows a typical SPC chart based on sensor data from a semiconductor manufacturing tool. Control limits are based on statistically improbable deviations from the data mean. They are shown as an Upper Control Limit (UCL) and a Lower Control Limit (LCL) in Fig. 2. Typically these limits are set at 3 or 4 times the standard deviation (sigma) from the mean of the data set, using a normal distribution model. This control technique has a number of limitations.

The first problem is that monitoring all SPC charts is not scalable, since there can be ten's of sensors per tool and several hundred tools in the fab. The second problem is that individual sensor outputs can stray outside control limits, with no apparent effect on the process output and/or process inputs can remain within control limits but process output can drift out-of-control due to changes in the process conditions. This is because the processing tools are typically complex and their output depends on their combined inputs as well as the conditions of the tool itself. It is for this reason that the semiconductor fab usually uses regular process quality sampling on test wafers since this is at least predictive of yield. For example, test wafers are frequently run to check process quality such as film stress in the case of a CVD process or critical dimension (CD) in the case of an etch process. This is known to be a very expensive approach to process control, since running test wafers and halting real production to test process quality negatively impacts factory yield and productivity. The third problem relates to the difficulty of setting SPC limits on the tool sensors. The SPC approach is statistical and assumes normally distributed data. This is generally not the case. Tool and sensor drift as well as normal tool interventions such as preventive maintenance

(PM) activity result in a data set which is not normally distributed.

Fig. 3 shows two data streams for output parameters 1 and 2 from a sensor in an oxide etch tool over a period of about 1100 wafers, during which time a pressure fault was detected at wafer number 1018. The fault was caused by a defective pressure controller. Two preventative maintenance wet-cleans were carried out in the interval preceding the fault. These PM events and chamber cycling effects are clearly visible in the raw data. It will also be seen that the data is highly non-normal, with auto-correlation and discontinuities. The SPC approach therefore cannot handle this data effectively and significant events can be lost in the data. Indeed, in the example of Fig. 3, the fault which occurred at wafer 1018 is impossible to pick out of the data using the SPC approach.

Multivariate statistical techniques have been used in an attempt to offset the first two problems mentioned above (e.g. US Pat. No. 5479340). Multivariate techniques take into account not only the individual variance of the control parameters, but also their covariance. This addresses some of the shortfalls of SPC techniques in that the multivariate statistic can be used to compress the data and thus reduce the number of control charts resulting in a more scalable solution. For example, it is possible to replace a multitude of sensor data streams with a single statistic, such as a Hotelling T^2, which captures the individual sensor variance and sensor-to-sensor covariance. Using these techniques the number of control charts is greatly reduced and the single statistic is more representative of overall system health.

However, since the multivariate approach is statistically based, the third problem is not addressed. This is illustrated

in Fig. 4, which shows a Hotelling T^2 statistic based on the sensor data including the streams shown in Fig. 3 (as well as streams for many more sensor output parameters). As mentioned, there is only one fault event in this data set, that occurring on wafer 1018. All other data, including drift and PM discontinuities are normal. However, this single multivariate statistic reports a couple of statistical excursions with greater than 99% confidence because they deviate from statistically normal behaviour, but misses the real fault condition. The multivariate statistical approach has an additional shortcoming. The magnitude of the excursion is difficult to interpret, again because it is statistically based. A large deviation in the statistic may not necessarily correspond to a very significant process quality issue, whereas a small deviation may occasionally indicate a major process excursion.

A further issue arises when using the statistical approach in a multi-tool semiconductor manufacturing site. In practice, process chambers are not perfectly matched. Sensor responses on one chamber are not identical to sensor responses on another chamber of the same model. Therefore, a statistical fault detection model cannot be transferred from one chamber to another, as small differences in sensor response would trigger a false alarm. The statistical model needs to learned from chamber to chamber. This is a further limitation in the approach.

As mentioned above, as well as statistical monitoring of manufacturing equipment, process control in the semiconductor industry uses regular process quality sampling. Indeed, since yield is directly determined by process quality, ultimately this is the most robust technique. However, measuring the process quality of every wafer at every process step, in

particular taking measurements from the wafer, is prohibitive in terms of reduced factory throughput and cost of measuring equipment. US Pat. No. 5,926,690 describes a method for process control on an etch tool based on measuring CD (critical dimension) and controlling the process by varying etch time based on the measurement. A single process quality output, CD, is controlled by selectively altering a single process input, photoresist etch time. If the film measurement tool is integrated with the etch tool then the CD can be measured before and after every wafer is run and adjustments made on the fly. This method of process control relies on precise measurement of the CD and determining if a change is significant or not on all wafers or a reasonable statistical sample. However, the reliance on accurate determination of, in this case, CD, or in the general case, a process quality metric, makes the technique very expensive to operate. An alternative approach in which it is not necessary to have a precise measurement of a process quality metric would be advantageous.

Another concept for process control is described in US Pat. No. 6,174,450. In this case, a single process parameter, namely direct current bias, is controlled by varying RF power. The concept is that by fixing a particular process input, a particular process output will be better controlled. One problem with this approach is that the process output depends on several inputs and unless all are controlled, the process output cannot be inferred.

SUMMARY OF THE INVENTION

Accordingly, the present invention provides a method of process control as claimed in claim 1.

An embodiment of the invention provides a method for process control based on determining if a fault occurs on the tool and determining if the fault has any impact on process quality.

In the embodiment, detecting faults is based only on recognising a "fingerprint" of a fault state. That is, fault detection proceeds by comparing the present state of the manufacturing equipment with a library of undesired states. Only if the condition is recognised as a fault is it flagged. Therefore, there are essentially no false positives and both fault detection and fault identification can be synonymous. Furthermore, having determined that the present state matches a fault state, the magnitude of the fault is determined and compared with the fault tolerance of the tool for the particular process. Thus, the fault condition can be ignored if it has no effect on process output.

The preferred embodiment has the following advantages over the prior art:

(a) Faults are detected by a pattern recognition method so that statistical anomalies do not trigger false alarms,

(b) The robustness of the fingerprint identification is not compromised by normal interventions made by the user in the process environment, such as preventative maintenance

(c) The magnitude of a fault is easily interpreted and can be reported on scale of importance to a user,

(d) There is no necessity to rely on accurate continuous in-situ measurement of process quality, for example, by measuring product characteristics such as CD. This method predicts process quality based on determination of any fault that would effect process quality,

(e) The library of fingerprints is portable so that scalability across sets of tools is possible.

BRIEF DESCRIPTION OF THE DRAWINGS

An embodiment of the invention will now be described, by way of example, with reference to the accompanying drawings, in which:

Fig. 1 depicts a typical semiconductor manufacturing tool with input settings and sensor outputs indicating equipment state;

Fig. 2 shows a statistical process control chart based on one of the sensor outputs;

Fig. 3 shows unprocessed sensor data over a period of time which includes preventive maintenance events and a real fault;

Fig. 4 shows a multivariate Hotelling T^2 process control chart based on a selection of tool sensor outputs;

Fig. 5 shows sensor output responses as a function of some typical process inputs;

Fig. 6 shows an example of correlation of sensor output with process input;

Fig. 7 shows a typical fault fingerprint constructed from fifteen sensor parameters;

Fig. 8 shows an example of correlation of process output with process input; and

Fig. 9 is a flow diagram of the present embodiment.

DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS

A method for process control of semiconductor manufacturing equipment comprises first determining a tool profile for each tool on which the invention is to be applied. In this embodiment, the tool profile is constructed from a plurality of tool sensor data. The sensor data can be multidimensional data from a single sensor or data from a set of sensors but in either case the data must be sensitive to tool-state and process-state changes. The important criterion is that the sensor data has sufficient dimensions to permit a plurality of different fingerprints to be defined for a respective plurality of different fault conditions. As used herein, a "fingerprint" is a set of sensor data which defines a particular state of the equipment - thus a fault fingerprint means a set of sensor data defining the state of the equipment in a fault condition.

Fig. 5 shows a portion of a tool profile for a particular plasma etcher. The response of 15 sensor outputs A1…A15 is shown for changes in each of two tool inputs. In this case sensor outputs are values for voltage, current and phase for five RF harmonics produced through RF excitation of the plasma and the tool inputs are RF power and process pressure. It will be seen that each sensor output value changes according to which process input has changed. For example, the output value A8 will decrease as delivered RF power increases but the value increases as pressure increases. Thus, especially when all sensor outputs are taken into account, a change in process pressure will be different and distinguishable from a change in delivered RF power. If many of the tool inputs are changed in a design of experiments then a complete tool profile comprising a set of sensor responses for process inputs can be established.

The invention relies on the reliability of sensor outputs to predict process-input values independently of the nominal settings of the input values. Fig. 6 shows a plot of a typical process input value, in this case RF power, versus the input value predicted from tool sensor outputs such as the response curves of the plasma etcher RF sensors of Fig. 5. It can be seen that in this case there is typically good correlation between the actual input and the predicted value of that input based on the sensor output data. Thus, the tool sensors can be used to accurately predict at least one tool input. So for example, in a fault condition, even though an operator may have set RF power to a nominal value, sensor data can provide a more reliable measure of the RF power delivered than the equipment controlling the delivery of the RF power.

As noted in US Patent No. 6,441,620, the tool profile can be used to apply a signature to a particular input. Thereafter, if the sensor outputs change and those changes match the changes expected from the set of learned response curves, then the fault root cause is immediately classifiable. However, US Patent No. 6,441,620 is only useful in diagnosing a fault once it has been detected for example by testing a product after processing; it cannot detect a fault as it is happening or when it is likely to happen.

As will be explained below, in the present method, a fault fingerprint is classified before a fault is encountered and this procedure ensures the method is very robust in detecting such faults.

Once the tool profile has been built, a library of known fault fingerprints is generated by either simulating faults e.g. by forcing a change in tool inputs and measuring the change in sensor outputs; by learning fault fingerprints as new faults

occur; or by importing fault fingerprint data from other tools. This last option is highly advantageous as it avoids time spent learning a model for each tool in the manufacturing plant.

In the embodiment, fault fingerprints are stored as differences in sensor output values from their tool profile values for nominal process input values. Fig. 7 is a visual representation of typical changes in the sensor data representing a fault fingerprint, as compared to data from the same sensor(s) in the absence of the fault. For example, a fault such as RF Power drifting above its nominal value may be characterised by a fault fingerprint comprising a negative value for A8, a positive value for A9, etc. These differences are referred to as vectors, since each has a magnitude (length of arrow in Fig. 7) and a direction (plus or minus).

A tool profile is required for each tool as the absolute values for sensor outputs are assumed to vary from tool to tool. However, the preferred embodiment is based on the assumption that the rate of change (slope in Fig. 5) of sensor outputs will be substantially the same from one tool of the same type to another. This enables fault fingerprints to be validly ported from one tool to another.

Finally a fault condition is determined by comparison of the present tool state in terms of the deviation of measured sensor output values from their nominal values as indicated by the tool profile, Fig. 5, with the fingerprints for any known fault states, Fig. 7. Each set of vectors representing a fault stored in the fault library is correlated with the corresponding set of vectors for the present tool state and a fault is detected if there is a significant match between the present tool state and a tool state defined by a set of

vectors representing a fault stored in the library. If the deviation matches a fingerprint in the fault library then it is flagged.

It can be seen from Fig. 3 that the variation in the individual sensor outputs from run to run can be relatively large; however, in this method unless the variation in each of the individual sensors closely match a known variation pattern, i.e. a fault fingerprint, then it is ignored. If the sensor data has many dimensions, then the probability of a false match is negligible. Thus process control in this method proceeds by comparing the present condition to fault conditions and not to normal conditions and this makes the technique very robust.

It will also be seen from the above, that in order to detect a fault, the tool profile need only contain sensor output values for nominal process input values. However, as will be explained later, it necessary for determining the effect of the fault on process outputs to understand the rate of change of sensor outputs versus process inputs.

The embodiment can be applied to learn the fingerprints of any new faults that occur and add them to the fault library. When a new fault appears the plurality of tool sensors will report a change in state. On first occurrence, there will be no matching fingerprint in the fault library and the fault cannot be classified. Fingerprints of new faults can be added when the fault is confirmed independently, for example, by metrology. Thereafter, if this fault reappears, it is instantly classified. The method thus allows for continuous learning and expansion of the fault library.

As mentioned above, to accelerate learning, these changes, representing typical fault conditions, can also be induced. For example, the integrity of the hardware and process can be deliberately compromised so that these fingerprints are recorded and included. Examples might be induced air leak, omission of or mis-fitting of hardware components, wafer mis-placement and so on.

In the preferred embodiment, having flagged a fault, the next step is to determine if that fault will have an effect on process output.

It will be seen that the response curves of Fig. 5 relate magnitude in sensor output change to magnitude of process input change.

Fig. 8 shows a set of plots showing dependence of process output on process input. These dependencies are typically well known for a given manufacturing tool. The pair of horizontal dashed lines correspond to a "window" within which the respective metric must lie for the product to meet its target specification. In this case, an etch process, the target specifications are for a post-etch CD (critical dimension) of between 101nm and 103nm. Thus, if the method as described above indicates that a fault has occurred and that, for example, the fault is a deviation in HBr flow of 15sccm from the set point of 130sccm, then the impact on CD is to produce CDs wider than tolerated by the target specifications. Therefore, a fault is flagged and the process is stopped. Now, since the operator knows where the fault lies, s/he can proceed to fixing the fault immediately.

Thus, it is possible to predict not only that a certain fault has occurred, but because the size of the fault i.e. the

change in process output caused by the deviation in process input, can be determined, this can then be used to estimate impact on process output quality.

Referring now to Fig. 9 which shows the preferred embodiment in more detail, tool profile data is saved as a plurality of response curves of the kind shown in Fig. 5 relating tool state (e.g. RF power, gas flow) to sensor output (e.g. voltage, current, phase), step 20. Fault condition data is captured and added to a fault library, step 22, by forced changes to process inputs; by adding additional fault fingerprint data to the library as faults occur; or as will be explained later by importing fault fingerprint data from other tools. This last option allows fault libraries to be rapidly populated. Each fingerprint such as that of Fig. 7 can be tagged as a process change of a certain magnitude.

In a production run, the product wafer is monitored via the plurality of sensor outputs and continually compared to the fault library fingerprints, step 24. The deviation of sensor outputs from their expected nominal values for a tool are compared with the corresponding values of each fingerprint. Although there are many possible approaches, in this embodiment, the comparison is based on mathematical correlation. However, Euclidean distance could also be employed. Thus, when a correlation value exceeds a given threshold or a Euclidean distance is below a given threshold, a fault condition is flagged, step 26. The impact of the fault is then determined, step 28, by comparing the magnitude of the fault, determined from the tool profile, Fig. 5, with process dependency data such as that shown in Fig. 8. If the fault is determined to have a negative or unacceptable impact on process output, step 30, then the tool is stopped and the identified problem is fixed, step 32.

It will be readily appreciated that the above process can be implemented by the person skilled in the art as a computer program having the relevant sensor values, after analog-digital conversion, as inputs.

It is to be understood that the changes in the process input parameters which the method is designed to detect are not those such as occur in response to changes in the relevant external input settings. Rather, it is changes which occur despite such input settings remaining nominally unchanged through some fault in the plasma process. For example, a mass flow rate sensor could develop a fault so that the actual rate of introduction of gas into a chamber varied from the value indicated by the sensor; or a match unit could absorb power so that the delivered RF power was less than that indicated on the power meter associated with the RF source.

The method described herein can also be used to determine changes in process conditions which are not necessarily faults but do affect process output and may become faults. For example, referring to Fig. 8, it is possible to predict changes in the process output within the desired output specification if the change in the process input is known. For example, the method described here can be used to determine a fault such as a change in process power. It may be determined that the change does not push the CD outside the desired specification but it may result in wider CDs. Although the final product is not catastrophically effected, it may indicate a trend so that the operator can predict a fault having a negative or unacceptable impact on process output before it occurs.

The method can also be used for closed loop process control since the magnitude of the fault is known. For example, in the case of Fig. 3 at wafer 1018, a pressure set point fault could be could be detected with the present method. The operator can either stop the process and fix the problem or elect to change the pressure based on the predicted change, ignoring the defective pressure gauge. Furthermore, in this example since the pressure change can be used to predict a change in process output, the operator can change the pressure based on the prediction of process output.

The invention is not limited to the embodiment described herein which may be modified or varied without departing from the scope of the invention.

CLAIMS:

1. A method of process control in manufacturing equipment, said manufacturing equipment having sensor(s) with output(s) indicative of the present state of equipment, comprising the steps of:

(a) establishing sensor data that are representative of a state of the equipment under a fault condition ("fault fingerprint"),

(b) storing said data in a fault fingerprint library,

(c) monitoring the present state of equipment using said sensor(s),

(d) detecting a fault based on a comparison of the present state data with fault fingerprints in said fault library.

2. The method claimed in claim 1, wherein said detecting step comprises comparing a difference between said present state data and said fault condition data with a predetermined threshold.

3. The method claimed in claim 2, wherein said difference is determined by correlation between a set of vectors representing the deviation of sensor data from nominal values for the fault fingerprint and the corresponding set of vectors representing the deviation of sensor data from nominal values for the present state.

4. The method claimed in claim 2, wherein said difference is a Euclidean distance between a set of vectors representing the deviation of sensor data from nominal values for the fault fingerprint and the corresponding set of vectors representing the deviation of sensor data from nominal values for the present state.

5. The method claimed in any preceding claim, further comprising predicting the impact of said fault on a particular process output.

6. The method claimed in any preceding claim, further comprising controlling equipment input(s) to compensate for said fault.

7. The method claimed in any previous claim, wherein the fault fingerprint is derived from a tool profile comprising a set of equipment input versus sensor response curves.

ABSTRACT

A method of fault identification on a semiconductor manufacturing tool includes monitoring tool sensor output, establishing a fingerprint of tool states based on the plurality of sensors outputs, capturing sensor data indicative of fault conditions, building a library of such fault fingerprints, comparing present tool fingerprint with fault fingerprints to identify a fault condition and estimating the effect of such a fault condition on process output. The fault library is constructed by inducing faults in a systematic way or by adding fingerprints of known faults after they occur.

(Fig. 9)

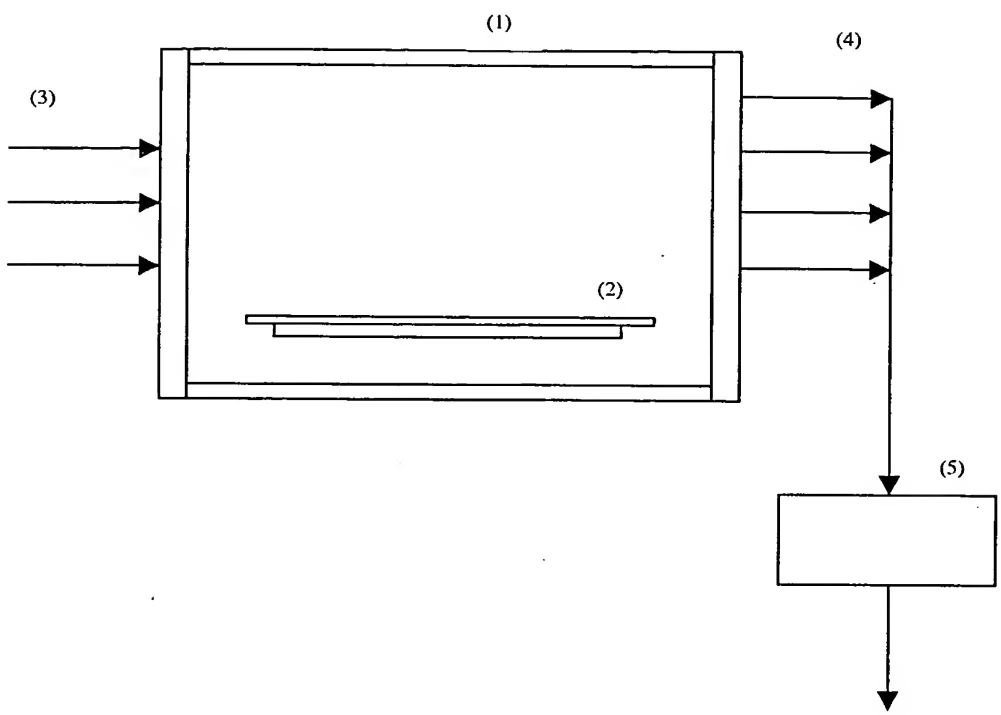


Fig. 1 (prior art)

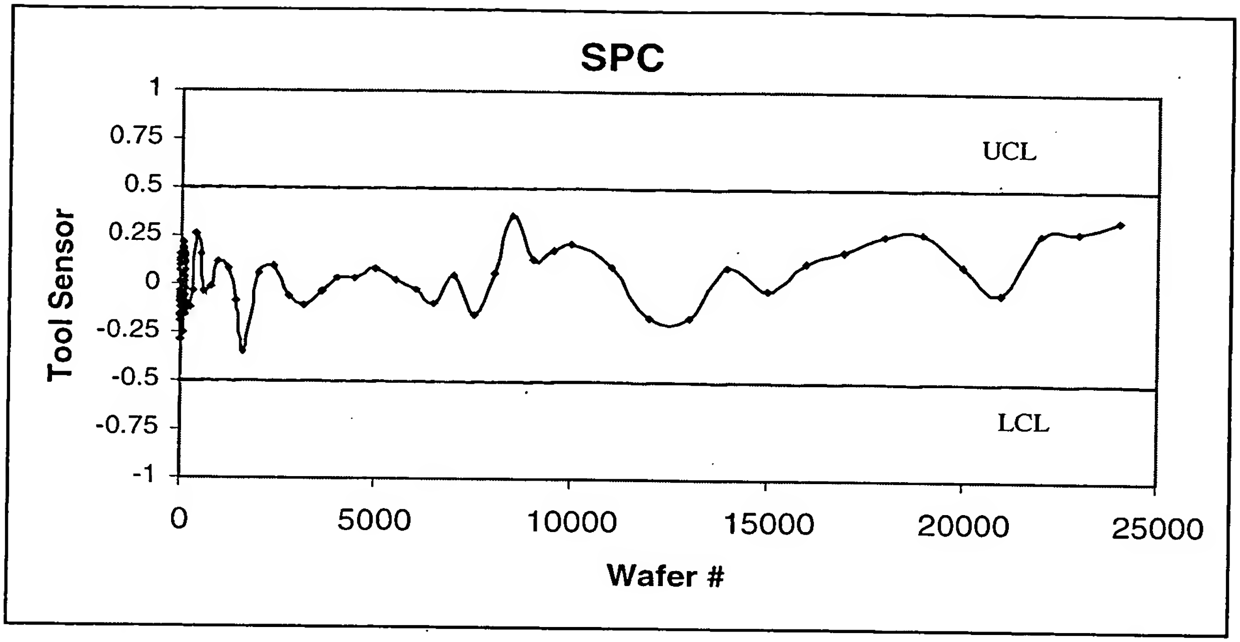


Fig. 2 (prior art)

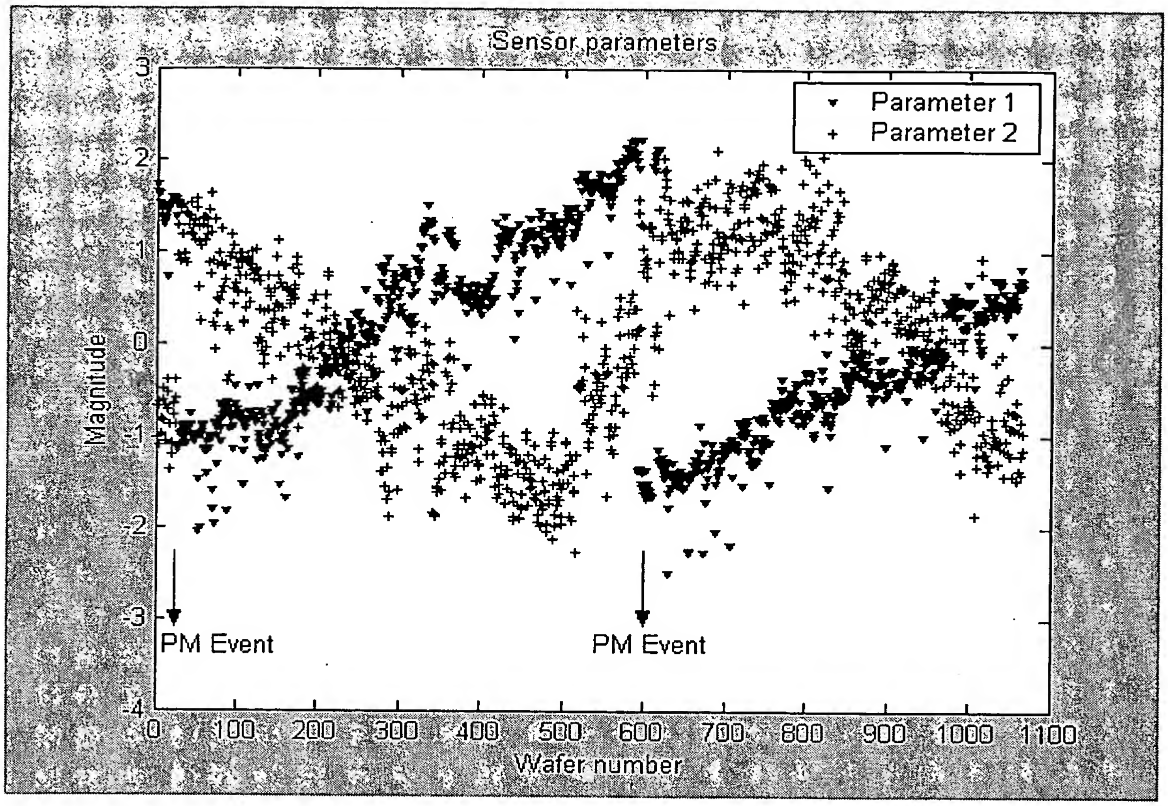


Fig. 3 (prior art)

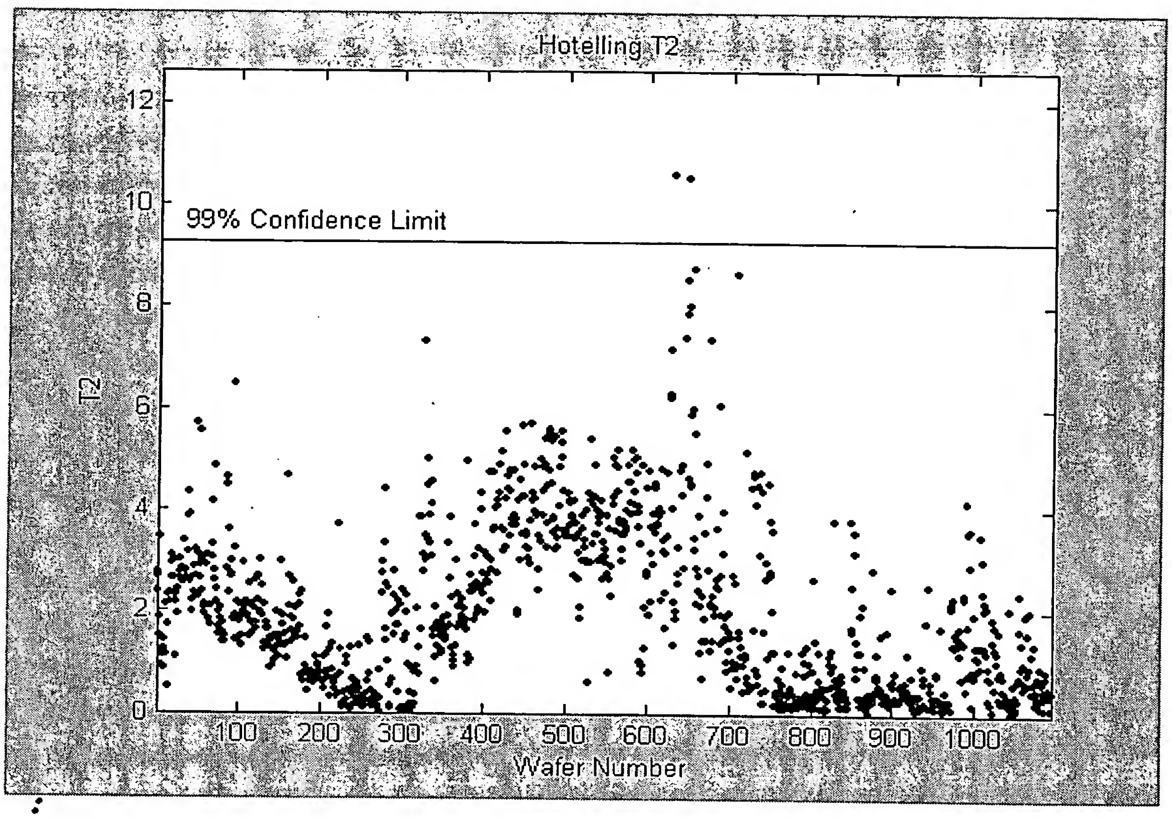
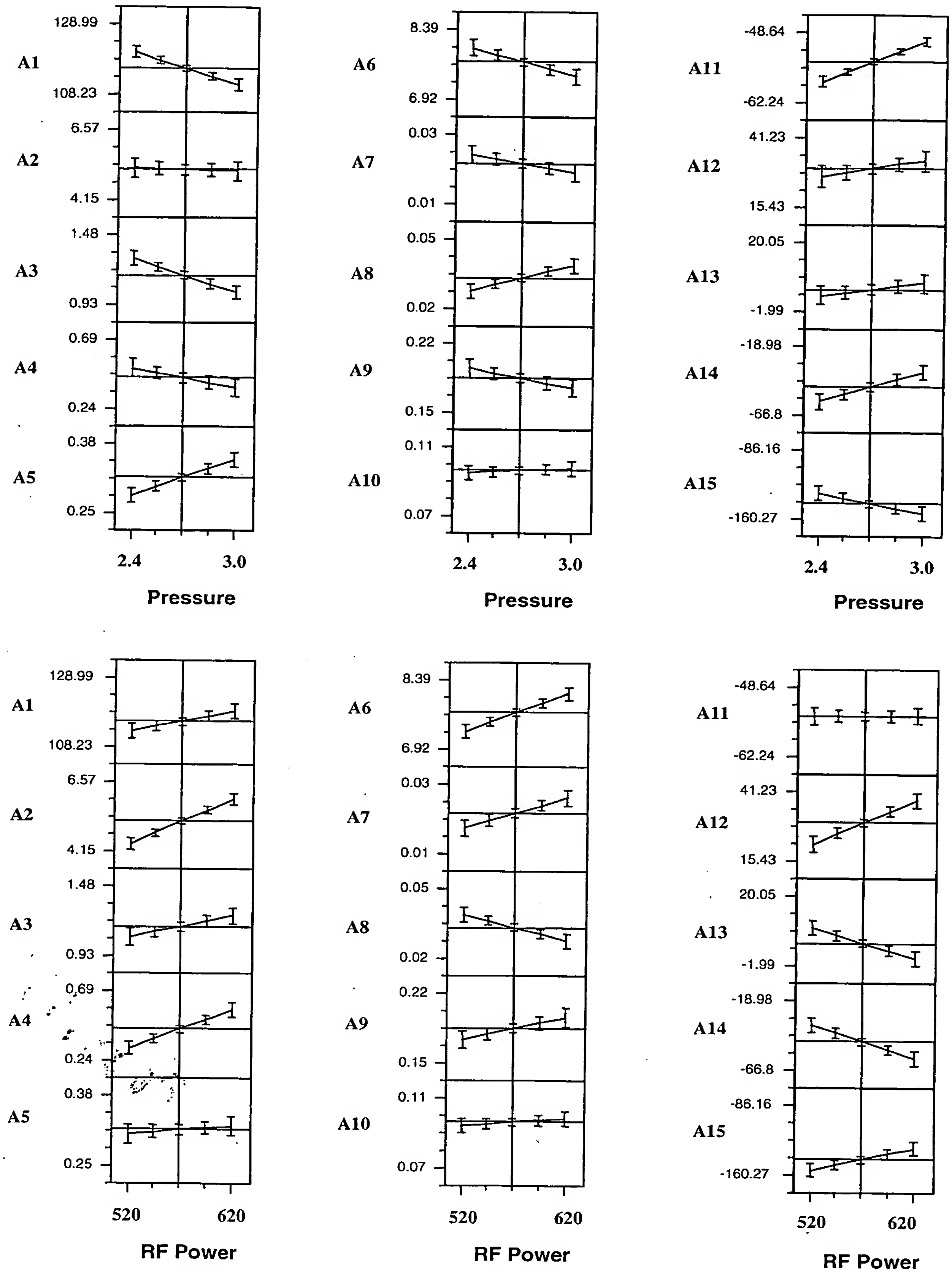


Fig. 4 (prior art)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15.43
20.05
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Pressure
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620
RF Power

Fig. 5

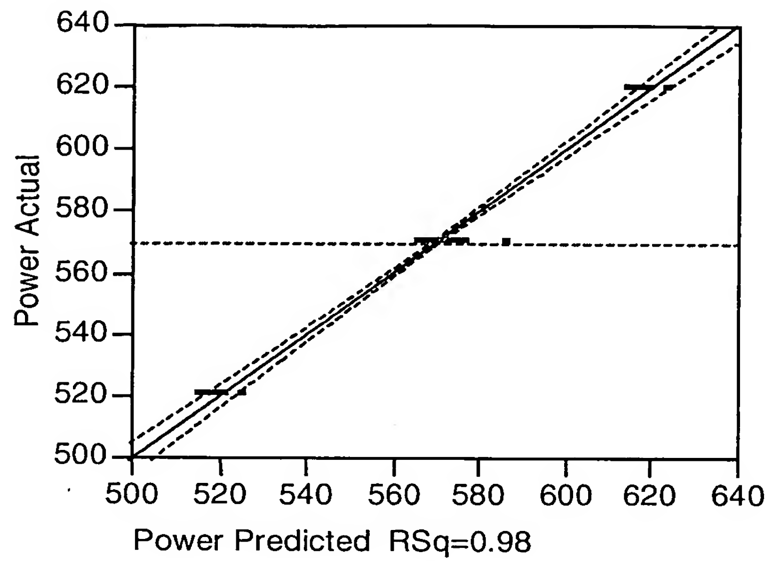
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Fig. 6

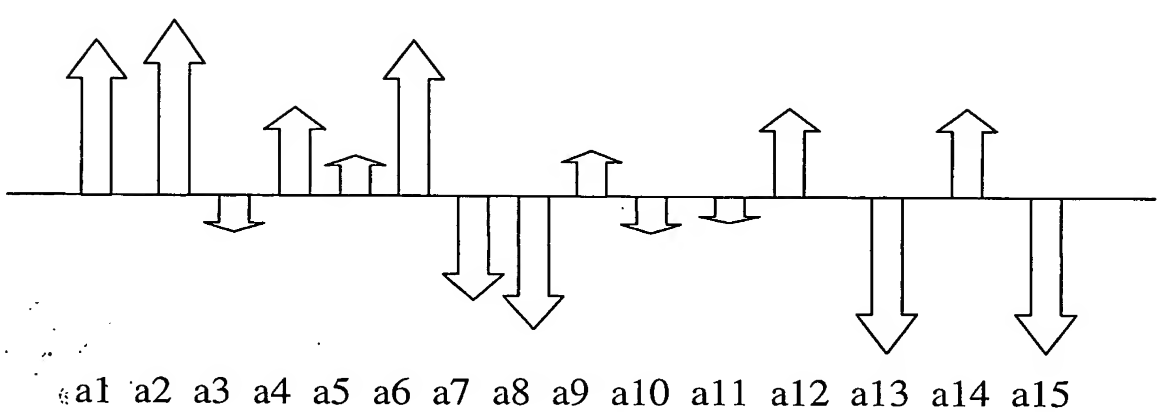
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Fig. 7

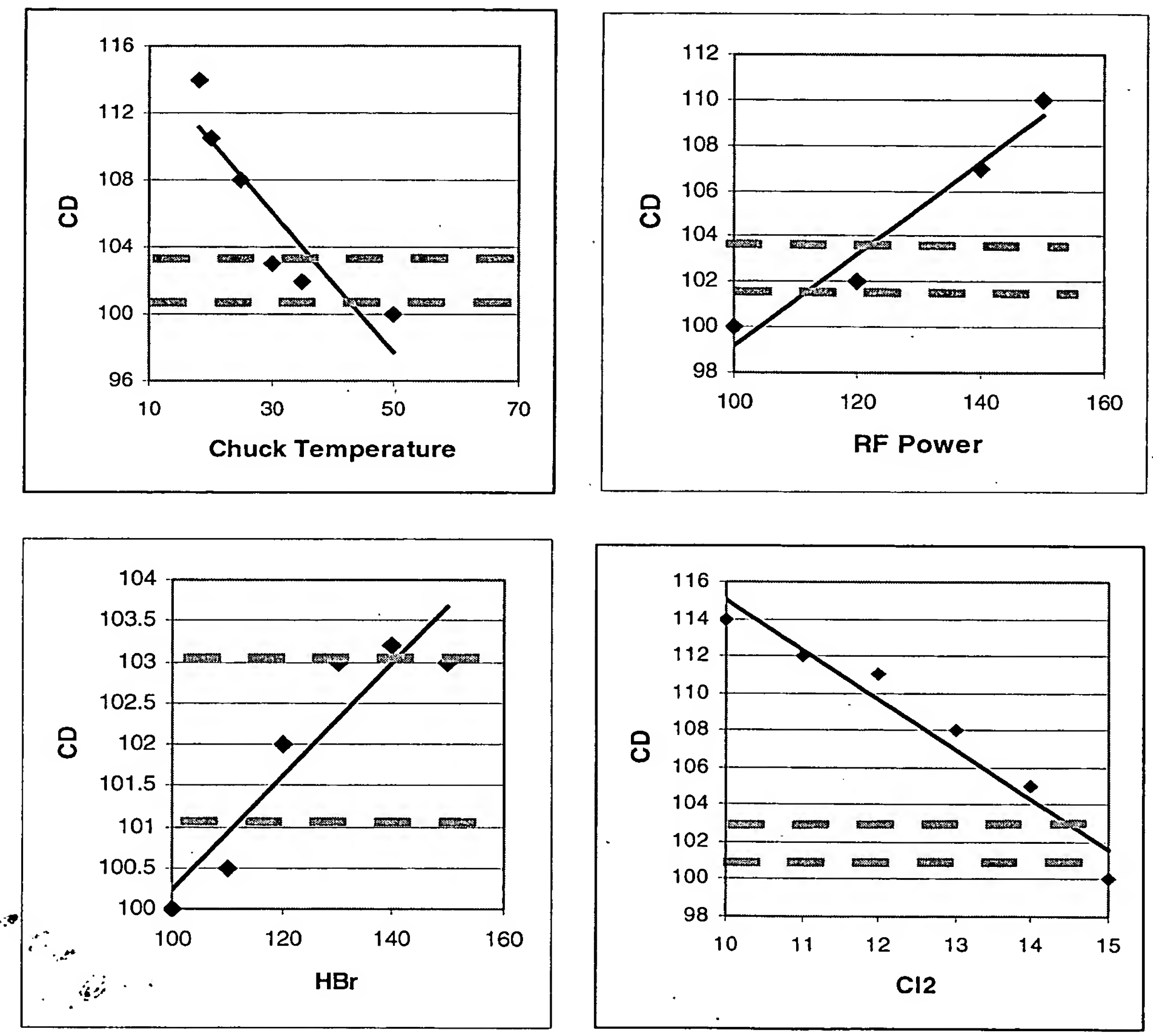
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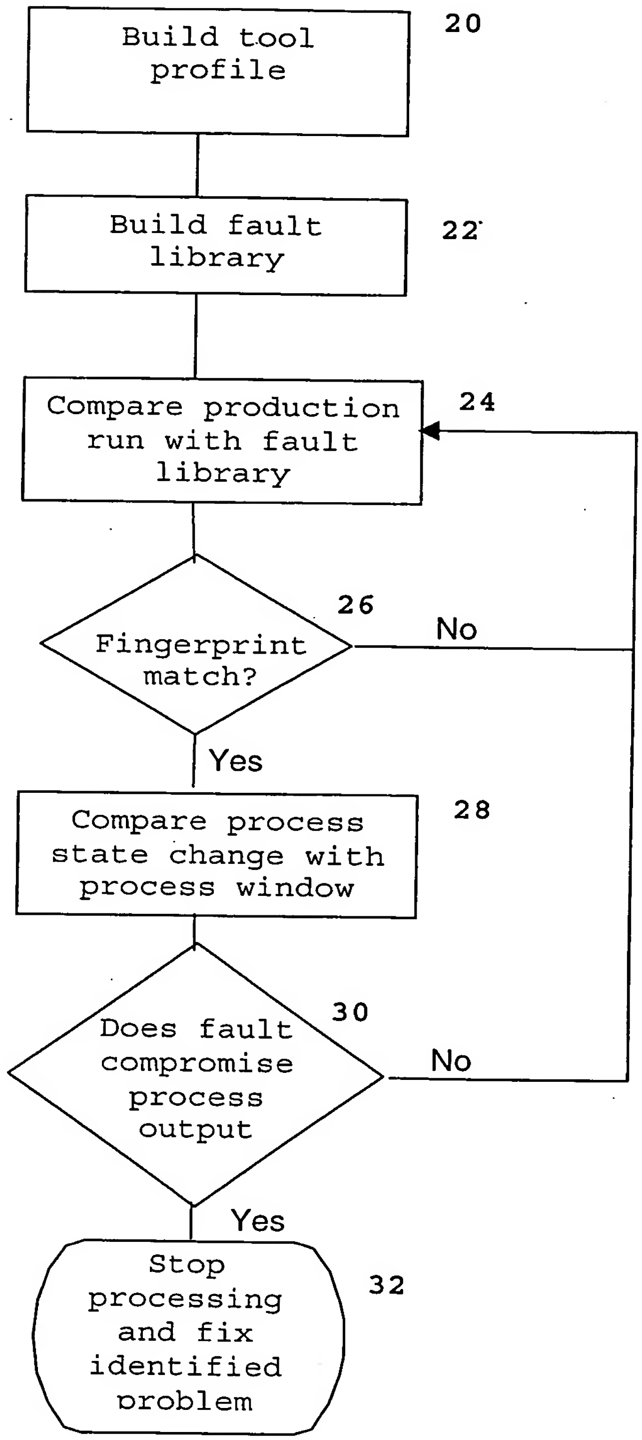
Fig. 8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20
Build fault library
22
Compare production run with fault library
24
Fingerprint match?
26
No
Yes
Compare process state change with process window
28
Does fault compromise process output
30
No
Yes
Stop processing and fix identified problem
32

Fig. 9